5

Machine Tool Monitoring and Control

Kourosh Danai
University of Massachusetts, Amherst

5.1 Introduction

Machine tool monitoring and control are essential for automated manufacturing. Monitoring is necessary for detection of a process anomaly to prevent machine damage by stopping the process, or to remove the anomaly by adjusting the process inputs (feeds and speeds). A process anomaly may be gradual such as tool/wheel wear, may be abrupt such as tool breakage, or preventable such as excessive vibration/chatter. Knowledge of tool wear is necessary for scheduling tool changes; detection of tool breakage is important for saving the workpiece and/or the machine; and identifying chatter is necessary for triggering corrective action. One difficulty in machine tool monitoring stems from the limited sensing capability afforded by the harsh manufacturing environment. Sensors can seldom be placed at the point of interest, and when located at remote locations they do not provide the clarity of measurement necessary for reliable monitoring. This limited sensing capability is often compensated for by using multiple sensors to enhance reliability. Another difficulty in machine tool monitoring is the absence of accurate analytical models to account for changes in the measured variables by variations in the cutting conditions. Such changes are often attributed to process anomalies by the monitoring system, which result in false alarms.

Machine tool control is motivated by two objectives: (1) process regulation, so as to preempt excessive forces, correct a process anomaly, or reduce contouring errors; and (2) process optimization, for the purpose of improving the quality of the part or reducing operation time based on feedback from the process.

The aim of this chapter is to provide a conceptual survey of machine tool monitoring and control. As such, no attempt has been made to acknowledge all the research in this area, and the citations are included mainly to provide representative examples of various approaches.

5.2 Process Monitoring

Process monitoring is generally performed through the analysis of process measurements. For this purpose, a process variable or a set of variables (e.g., force, power, acoustic emission, feed motor current) is measured and processed on-line to be compared against its expected value. Any deviation from this expected value is attributed to a process anomaly. Expected values of measurements are either determined according to an analytical model of the process[1] or established empirically.[2] The advantage of using analytical models is that they account for changes in the machine inputs such as feeds and speeds. The disadvantage of analytical models is that they are often not accurate and need to be calibrated for the process. Establishing the expected values of measurements empirically is simpler and more straightforward. However, the empirical values are only suitable for particular operations and cannot be extrapolated to others. To provide a representative sample of approaches used in this area, tool wear estimation, tool breakage detection, and chatter identification are discussed as the most investigated topics in machine tool monitoring.

5.2.1 Tool Wear Estimation

Flank wear directly influences the size and quality of the surface.[3] Flank wear can affect fatigue endurance limit by affecting surface finish, lubrication retention capability by changing the distribution of heights and slopes of the surface,[4] and other tribological aspects[5,6] by affecting the topography of the machined surface. Therefore, information about the state of flank wear is sought to plan tool changes in order to avoid scrapping or manipulating the feed and cutting speed in-process to control tool life.[7]

Methods used for flank wear estimation can be classified as either direct or indirect.[8] Direct methods measure flank wear either in terms of material loss from the tool[9] or by observing the worn surface using optical methods.[10] Direct methods are generally more reliable, although they are not convenient for in-process use in a harsh manufacturing environment. Indirect methods, on the other hand, estimate the flank wear by relating it to a measured variable such as the change in size of the workpiece,[11] cutting force,[12] temperature,[13] vibration,[14] or acoustic emissions.[15] The ideal measured variable in the indirect method is one that is insensitive to process inputs. For example, noncontact methods have been recently developed for surface roughness measurement,[16,17] which will undoubtedly have an impact on on-line estimation of tool wear.

Among the measurements used for indirect flank wear estimation, acoustic emission (AE) and the cutting force have been the most popular due to their sensitivity to tool wear and reliability of measurement. The cutting force generally increases with flank wear due to an increase in the contact area of the wear land with the workpiece. Zorev[18] and De Filippi and Ippolito[19] were among the first who demonstrated the direct effect of flank wear on the cutting force, which motivated separation of the cutting force signal into two components, one associated with the unworn tool and the other associated with tool wear. The unworn tool component is usually estimated at the beginning of the cut with a new tool, and then subtracted from the measured force to estimate the wear affected component. This method can provide relatively accurate estimates of flank wear so long as the cutting variables (feed, speed, and depth of cut) remain unchanged. However, when the cutting variables change, due to such factors as the geometric requirements of the part or manipulation of the operating parameters, the identification of the wear affected component becomes difficult. In such cases, either the effect of the manipulated cutting variable on the cutting force is estimated by a model[1] and separated to identify the wear affected component,[10,20] or the wear affected component is estimated from small cutting segments where the cutting variables remain unchanged.[21] In either case, recursive parameter estimation techniques, which require persistent excitation of the cutting force to guarantee parameter convergence, are used for identification purposes. The requirement for persistent excitation is relaxed,[12] by measuring the cutting force during the transient at the beginning of the cut when the tool engages the workpiece. During this transient, the sharp tool chip formation component, which is proportional to the cross-sectional area of the cut normal to the main cutting velocity, takes a wide range of values, from zero to the steady-state value (product of the feed and depth of cut). The method uses the variations of the cross-sectional area of the cut during this short time interval when flank wear is essentially constant to tune the model and estimate its parameters. It has been shown in laboratory experiments that the residual force components in the axial and tangential directions increase linearly with the wear land width, which can be used to estimate flank wear.[12]

Similar to the cutting force signal, acoustic emission has been studied extensively for flank wear estimation, where various statistical properties of the AE signal have been shown to correlate with flank wear.[15] To define more clearly the effect of flank wear, statistical pattern classification of AE signal in frequency domain has been utilized as well.[22,23]

Despite the considerable effort toward estimation of flank wear from a single variable, single sensor measurements do not seem to be robust to varying cutting conditions. This has motivated integration of multiple measurements through artificial neural networks.[24,25] Artificial neural networks have the ability to represent patterns of fault signatures by complex decision regions without reliance on the probabilistic structure of the patterns. Thus, they are powerful tools for fault detection/diagnosis. Generally, a neural network is trained to identify the tool wear pattern by supervised learning from samples of measurements taken at various levels of tool wear. Therefore, the ability of neural networks to form reliable wear patterns depends not only on their topology, but the extent of their training. In cases such as machining where adequate data are not available to select the topology of the network or to provide the tool wear patterns for a wide range of cutting conditions and material/tool combinations, these networks are not practical.

A remedy to supervised learning is the application of unsupervised neural networks[26] that can form pattern clusters of data without a known target for each input vector. These networks use prototype vectors to characterize each category, and then classify input vectors within each category according to their similarity to these prototype vectors. While there is a need to provide data from each category to these networks in order to form the prototype vectors, the demand for training is considerably less. Therefore, unsupervised networks have better potential for on-line utility in machine tool monitoring. A comprehensive demonstration of unsupervised neural networks in tool failure monitoring is provided by Li et al.,[27] who applied an array of adaptive resonance theory (ART2) networks[28] to detect tool wear, tool breakage, and chatter using vibration and AE measurements.

5.2.2 Tool Breakage Detection

Fracture is the dominant mode of failure for more than one quarter of all advanced tooling material. Therefore, on-line detection of tool breakages is crucial to the realization of fully automated machining. Ideally, a tool breakage detection system must be able to detect failures rapidly to prevent damage to the workpiece, and must be reliable to eliminate unnecessary downtime due to false alarms.

Several measurements have been reported as good indicators of tool breakage.[29] Among these, the cutting force,[30] acoustic emission,[31,32] spindle motor current,[33] feed motor current,[34] and machine tool vibration[35,36] have been investigated extensively for their sensitivity to tool breakage. In general, to utilize a measurement for tool breakage detection, two requirements need to be satisfied. First, the measurement must reflect tool breakage under diverse cutting conditions (e.g., variable speeds, feeds, coolant on/off, workpiece material). Second, the effect of tool breakage on the measurement (tool breakage signature) must be uniquely distinguishable, so that other process irregularities such as hard spots will not be confused with tool breakage. The tool breakage signature is commonly in the form of an abrupt change, in excess of a threshold value. Despite considerable effort,[37,38] reliable signatures of tool breakage that are robust to diverse cutting conditions have not yet been found from individual measurements.

To extract more information from individual measurements to improve the reliability of tool breakage signatures, pattern classification techniques have been utilized. One of the earliest efforts was by Sata et al.[39] who related features of the cutting force spectrum such as its total power, the power in the very low frequency range, and the power at the highest spectrum peak and its frequency to chip formation, chatter, and a built-up edge. It was shown that the cutting force measurement alone provides sufficient information for unique identification of the above phenomena. Another important work in this category is by Kannatey-Asibu and Emel[22] who applied statistical pattern classification to identify chip formation, tool breakage, and chip noise from acoustic emission measurements. They reported a success rate of 90% for tool breakage detection. The only drawback to spectrum-based tool breakage detection is the computational burden associated with obtaining the spectrum, which often precludes its on-line application.

The alternative to single-sensor-based pattern classification is the multi-sensor approach using artificial neural networks for establishing the breakage patterns.[24] However, as already mentioned for tool wear estimation, the utility of neural networks for tool breakage detection is limited by their demand for expensive training. A pattern classifier that requires less training than artificial neural networks is the multi-valued influence matrix (MVIM) method[40] which has a fixed structure and has been shown to provide robust detection of tool breakages in turning with limited training.[41]

Unsupervised neural networks have also been proposed for tool breakage detection in machining.[42] The two predominant methods of unsupervised learning presently available for neural networks are Kohonen's feature mapping and adaptive resonance theory (ART2).[28] Kohonen's method of feature mapping establishes the decision regions for normal and abnormal categories through prototype vectors that represent the centers of measurement clusters belonging to these categories. Classification is based on the Euclidean distance between the measurements and each of the prototype vectors. While Kohonen's method forms the prototype vectors far enough from each other to cope with variations in the tool breakage signature, it requires one or more sets of measurements at tool breakage to establish the prototype vector for the abnormal category. The other method of unsupervised learning, the adaptive resonance theory (ART2), classifies the measurements as normal unless they are sufficiently different. When applied to tool breakage detection, it does not require any samples of measurements to be taken at tool breakage. ART2, however, may not cope effectively with varying levels of noise associated with different sensors, and may classify multiples of a prototype within the same category, so it may produce misclassification. A hybrid of the above pattern classifiers is the single category-based classifier (SCBC)[43] that performs detection by comparing each set of measurements against their corresponding prototype values for their normal category and detects tool breakage when the measurements are sufficiently different from their normal prototypes. Another variant of ART2 applied to tool breakage detection is a network consisting of an array of ART2 networks, each classifying the pattern associated with an individual sensor.[27]

5.2.3 Chatter Detection

Chatter is the self-excited vibration of the machine tool that reflects the instability of the cutting process. Chatter is often a serious limitation to achieving higher rates of removal, as it adversely affects the surface finish, reduces dimensional accuracy, and may damage the tool and machine. Therefore, machine tool chatter needs to be detected rapidly and corrected before it damages the workpiece, tool, or the machine.

Several variables have been studied for detection of chatter. These include the cutting force signal, displacement or acceleration of a point in the vicinity of the tool–workpiece interface, or the sound emitted from the machine. Delio et al.[44] claim that sensor placement and the frequency response limitations of the transducer are the two major difficulties in detection of chatter. They also claim that sound provides the most reliable and robust signature for chatter. While chatter has been investigated extensively, most of the efforts have been directed toward prediction of chatter rather than its detection. The approaches used for chatter detection mirror those employed for tool breakage detection, except that analysis is performed primarily in frequency domain where the effect of vibration is most pronounced.

5.3 Process Control

The advent of open-architecture control provides a natural framework for implementation of control systems in machine tools.[45] Machine tool control is generally performed at two levels: (1) servo-control to execute the command motion dictated by interpolators for following a prespecified contour, or (2) supervisory control to continually adjust the process variables for the purpose of either regulating the process against disturbances/detected anomalies, or optimizing performance.[46] Process regulation is often incorporated as the next step to process monitoring, whereby the controller attempts to correct, if possible, the detected anomaly. Process optimization, on the other hand, is implemented to enhance productivity based on an assessment of process and part quality constraints.

5.3.1 Control for Process Regulation

Control for process regulation has been attempted for one of the following reasons: maintaining constant power or force, safeguarding against chatter, or correcting machine tool errors. The most regulated process variable in machining has been the cutting force, mainly for its ease of measurement on-line, and its reflection of process anomalies such as tool breakage and chatter. While there have been differences in format and the underlying models used, most of the controllers designed for force regulation have used a dynamic model of the cutting force with respect to the manipulated variable (i.e., feed or speed) and have employed parameter estimation to adapt the model to changing process conditions.[47-53] Within this category, Furness et al.[54] regulated the torque in drilling to avoid possible chipping of the drill tips, stall of the spindle motor, thermal softening of the tool, or torsional failure of the drill.

Among the first to design a controller for elimination of chatter were Nachtigal and Cook[55] who used the cutting force signal as feedback to control the position of the tool for increased stability. They designed their controller on a fixed model of the machine tool–workpiece dynamics. As a next step and to account for parameter uncertainty in that model, Mitchell and Harrison[56] integrated an observer in their control system to estimate the cutting tool motion on-line for feedback to the control system. Active control of chatter is, by and large, an identification problem, because once the presence of chatter is detected, the solution seems to be straightforward.[44,57]

Another active area of research in process regulation is error correction. The accuracy of a machined part is generally attributed to geometric and kinematic errors of the machine spindle, thermal effects, and static and dynamic loading of the drives.[58] Therefore, considerable effort has been directed toward error compensation by modifying the tool position. Two fundamental approaches have been used for reducing contouring errors:[46] (1) by reducing the tracking error of individual axes, and (2) by reducing contour error which is defined as the error between the actual and desired tool path. As in force-regulation problems, a common approach used in many of these systems is utilization of parameter estimation to update the servo-models in the presence of variable loading and friction (e.g., see Tsao and Tomizuka[59]). The literature on tool error compensation is quite extensive and is not surveyed here in the interest of space. Interested readers are referred to Koren[46] or Tung et al.[60] for specific examples and an overview of the research in this area.

5.3.2 Control for Process Optimization

The adaptation of process variables for the purpose of enhancing process efficiency is addressed within the area of control for process optimization.[1] Process efficiency is generally defined in terms of reduced* production cost or cycle time. Under deterministic conditions (no modeling uncertainty

*Control for process optimization has also been referred to as adaptive control optimization (ACO) in the manufacturing engineering literature.[46]

and noise), there would be no need for a controller, as the optimal process inputs (feeds and speeds) could be determined by nonlinear programming.[61] In view of the highly complex nature of machining processes, however, the process inputs need to be changed iteratively in response to measurements of process and part quality constraints. This interactive approach to process optimization is adopted to enable the control system to maintain constraint satisfaction despite modeling uncertainty arising from (1) the diversity of machining conditions due to variations in material properties, tool/wheel type, and lubrication, (2) the stochastic nature of these processes caused by material inhomogeneity, workpiece misalignment, and measurement noise, and (3) process time variability due to tool wear.

The first attempt at control for process optimization was the Bendix system,[62] which was designed to continually maximize the machining removal rate through changes in both the feedrate and spindle speed in response to feedback measurements of cutting torque, tool temperature, and machine vibration. The Bendix System, however, was limited in applicability due to the need to estimate tool wear based on an accurate model. A subsequent advancement in control for process optimization was the Optimal Locus Approach,[63,64] which made it possible to forego estimation of tool wear. In this approach, the locus of the optimal points associated with various levels of tool wear is computed, and the optimal point is sought where process and part quality constraints become tight. The Optimal Locus Approach can avoid estimation of tool wear by using the tightness of constraints as the measure for optimality, but it still needs to rely on the accuracy of the process model for computing the optimal locus and determining *a priori* which constraints are tight at the optimum. Because the success of this approach depends on the premise that modeling uncertainty will have negligible effect on the accuracy of the optimal locus, it will produce suboptimal results when this premise is violated. A similar approach in drilling, but with several more constraints, was demonstrated by Furness et al.[65] by locating the feasible region of the process according to the pair of constraints active during each of the three drilling phases. In this application, the constraints were considered to be stationary, due to the absence of tool wear in short-duration drilling cycles.

One approach to coping with modeling uncertainty in process optimization is to calibrate (e.g., by parameter estimation) the closed-form solution of the optimal process inputs. This approach has been implemented in cylindrical plunge grinding where each cycle is moved closer to its minimum time based on a closed-form solution of the optimization problem according to a monotonicity analysis.[66] In this method, parameter estimation is used to cope with modelling uncertainty and process variability by continually updating the estimated optimal conditions using parameters estimated from the preceding grinding cycle. The basic requirement for this system is the availability of a relatively accurate model of the process that can be updated using parameter estimation. Such accurate modeling is possible for a few machining processes, but its extension to less-understood processes is difficult.

Another approach that uses an iterative strategy to process optimization but does not require accurate process models is the method of Recursive Constraint Bounding (RCB).[67] Like the Optimal Locus Approach, RCB assesses optimality from the tightness in the constraints using measurements of process and part quality after each workpiece has been finished (cycle). It also uses the model of the process to find the optimal point. However, unlike the Optimal Locus Approach, RCB assumes the model to be uncertain when determining which constraints are to be tight at the optimum and selecting the machine settings for each process cycle. It obtains the machine settings by solving a customized nonlinear programming (NLP) problem, and allows for uncertainty by incorporating conservatism into the NLP problem. This conservatism is tailored according to the severity of modeling uncertainty associated with each constraint. The repeated minimization of the objective function with a progressively less conservative model has been shown to lead to bound constraints and optimal machine settings.[68]

Empirical modeling using neural networks has also been proposed for coping with modeling uncertainty in process optimization.[69,70] In one case, separate neural networks are used to represent tool wear and the process, respectively, as a function of process variables (i.e., feed and speed), and the optimal point of the process is determined according to the neural network model and the estimate of tool wear.[69] In another approach, an iterative method to process optimization is adopted by using a neural network trained as an inverse process model to provide increasingly more optimal process variables.[70] One of the inputs to this neural network is an estimate of a cost function obtained from measurements of cutting force and vibration. Neural network modeling is appealing from the point of view of coping with process uncertainty; however, it has limited utility in manufacturing due to the expense associated with obtaining training data.

5.4 Conclusion

Machine tool monitoring and control provide the bridge between machining research and the production line. Nevertheless, despite years of research and the multitude of success stories in the laboratory, only a small amount of this technology has been transferred to production. It may be argued that the slowness in technology transfer is due to the complexity of machining processes and their incompatibility with the sensing technology. This is supported by the fact that most of the monitoring systems developed are specific to isolated problems, and cannot be integrated with other solutions to provide an effective monitoring system for all the process anomalies of concern. Similarly, it may be argued that most control systems developed in the laboratory use impractical or expensive transducers that are not suitable for the harsh production environment.

While complexity and sensing limitations are important impediments to technology transfer in monitoring, they are minor compared to the cultural barrier imposed by the stringent manufacturing environment. For implementation in production, monitoring and control systems need to be either retrofitted to the existing machine tools or incorporated into new machine tools. The first option will almost never happen because the savings from these systems rarely justify the loss from production downtime. The second option, while more plausible, has not broadly occurred either, mainly due to the cost competitiveness of the machine tool market. Three requirements need to be satisfied for inclusion of monitoring and control in machine tools: (1) the underlying sensors need to be nonintrusive and inexpensive, (2) the monitoring system needs to be comprehensive to detect every process anomaly possible in operation, and (3) both monitoring and control need to be perfectly reliable and robust to process variations. It is basically impossible to satisfy the above conditions, particularly the third one.

A compromise position is to incorporate monitoring and control for specific operations, based on the sensing capability already available on the machine tool. The presence of open-architecture control systems will be a significant boost to this solution, mainly due to the versatility these systems offer in software development and trouble shooting.

References

1. Danai, K. and Ulsoy, A. G., 1987, A dynamic state model for on-line tool wear estimation in turning, *ASME Journal of Engineering for Industry*, 109, 4, 396–399.
2. Du, R., Elbestawi, M. A., and Wu, S. M., 1995, Automated monitoring of manufacturing processes, Part 1: Monitoring methods, and Part 2: Applications, *ASME Journal of Engineering for Industry,* 117, 121–132.
3. Jetly, S., 1984, Measuring cutting tool wear on-line: some practical considerations, *Manufacturing Engineering*, July, 55–60.
4. Whitehouse, D. J., 1978, Surfaces — a link between manufacture and function, *Proceedings of the Institution of Mechanical Engineers*, 179–188.
5. Tonder, K., 1987, Effects of skew unidirectional striated roughness on hydrodynamic lubrication, *Wear*, 115, 19.
6. Wilson, W. R. D. and Sheu, S., 1988, Influence of surface topography on viscoplastic asperity lubrication, *Wear*, 124, 311.

7. Koren, Y. and Ulsoy, A. G., 1989, Adaptive control in machining, in *Metals Handbook*, ASM International, Cleveland, Ohio.
8. Cook, N. H., 1980, Tool wear sensors, *Wear*, 62, 49–57.
9. Cook, N. H. and Subramanian, K., 1978, Micro-isotope tool wear sensor, *CIRP Annals*, 27, 1, 73–78.
10. Park, J.-J. and Ulsoy, A. G., 1993, On-line flank wear estimation using an adaptive observer and computer vision, Part 1: Theory, Part 2: Experiment, *ASME Journal of Engineering for Industry,* 115, 30–43.
11. El Gomayel, J. I. and Bregger, K. D., 1986, On-line tool wear sensing for turning operations, *ASME Journal of Engineering for Industry*, 108, 44–47.
12. Nair, R., Danai, K., and Malkin, S., 1992, Turning process identification through force transients, *ASME Journal of Engineering for Industry*, 114, 1, 1–7.
13. Groover, M. P., Karpovich R. J., and Levy, E. K., 1977, A study of the relationship between remote thermocouple temperature and tool wear in machining, *International Journal of Product Research*, 25, 2, 129–141.
14. Martin, P., Mutels B., and Draiper, J. P., 1975, Influence of lathe tool wear on the vibrations sustained in cutting, 16th International Machine Tool Design and Research Conference.
15. Kannatey-Asibu, Jr., E. and Dornfeld, D. A., 1982, A study of tool wear in metal cutting using statistical analysis of acoustic emission, *Wear*, 76, 2, 247–261.
16. Coker, S. A., Oh, S. J., and Shin, Y. C., In-process monitoring of surface roughness utilizing ultrasound, *ASME Journal for Manufacturing Scientists and Engineers,* 120, 197–200.
17. Bradley, C., Bohlmann, J., and Kurada, S., 1998, A fiber optic sensor for surface roughness measurement, *ASME Journal for Manufacturing Scientists and Engineers,* 120, 359–367.
18. Zorev, N. N., 1966, Mechanics of contact on the clearance surface, in *Metal Cutting Mechanics*, Shaw, M. C. (Ed.), 129–180, Pergamon Press, Oxford, England.
19. De Filippi, A. and Ippolito, R., 1969, Adaptive control in turning: cutting forces and tool wear relationships for P10, P20, P30 carbides, *CIRP Annals*, 17, 377–379.
20. Danai, K. and Ulsoy, A. G., 1987, An adaptive observer for on-line tool wear estimation in turning, Part I: Theory, Part II: Results, *Mechanical Systems and Signal Processing*, 1, 2, 211–240.
21. Koren, Y., Ko, T., Ulsoy, A. G., and Danai, K., 1991, Flank wear estimation under varying cutting conditions, *ASME Journal of Dynamic Systems, Measurments, and Control*, 113, 2, 300–307.
22. Kannatey-Asibu, E. and Emel, E., 1987, Linear discriminant function analysis of acoustic emission signals for cutting tool monitoring, *Mechanical Systems and Signal Processing*, 4, 333–347.
23. Houshmand, A. A. and Kannatey-Asibu, E., 1989, Statistical process control of acoustic emission for cutting tool monitoring, *Mechanical Systems and Signal Processing*, 3, 4, 405–424.
24. Rangwala, S. and Dornfeld, D., 1990, Sensor integration using neural networks for intelligent tool condition monitoring, *ASME Journal of Engineering for Industry*, 112, 219–228.
25. Govekar, E. and Grabec, I., 1994, Self-organizing neural network application to drill wear classification, *ASME Journal of Engineering for Industry*, 116, 233–238.
26. Leem, C. S., Dornfeld, D. A., and Dreyfus, S. E., 1995, A customized neural network for sensor fusion in on-line monitoring for cutting tool wear, *ASME Journal of Engineering for Industry*, 117, 152–159.
27. Li, X. Q., Wong, Y. S., and Nee, A. Y. C., 1998, A comprehensive idenitification of tool failure and chatter using a parallel multi-Art2 neural network, *ASME Journal for Manufacturing Scientists and Engineers,* 120, 433–442.
28. Hertz, J., Krogh, A., and Palmer, R. G., Eds., 1991, *Introduction to the Theory of Neural Computation*, Addison-Wesley, Redwood City, CA.
29. Tlusty, J. and Andrews, G. C., 1983, A critical review of sensors for unmanned machining, *Annals of the CIRP*, 32, 2, 563–572.
30. Altintas, Y. and Yellowley, I., 1987, In-process detection of tool failure in milling using cutting force models, in *Sensors for Manufacturing*, ASME, New York, 1–16.
31. Moriwaki, T., 1980, Detection for tool fracture by acoustic emission measurement, *Annals of the CIRP*, 29, 1, 35–40.

32. Lan, M. S. and Dornfeld, D. A., 1984, In-process tool fracture detection, *ASME Journal of Engineering Materials and Technology*, 106, April, 111–118.
33. Matsushima, K., Bertok, P., and Sata, T., 1982, In-process detection of tool breakage by monitoring the spindle motor current of a machine tool, in *Measurement and Control for Batch Manufacturing*, ASME, New York, 145–154.
34. Altintas, Y., 1997, Prediction of cutting forces and tool breakage in milling from feed drive current measurements, *ASME Journal for Manufacturing Scientists and Engineers,* 119, 386–392.
35. Grieshaber, D., Ramalingam, R., and Frohrib, D., 1987, On real-time tool fracture in milling, *Proceedings of the 15th NAMRC*, May, 477–484.
36. Hayashi, S. R., Thomas, C. E., and Wildes, D. G., 1988, Tool break detection by monitoring ultrasonic vibrations, *Annals of the CIRP*, 37, 1, 61–64.
37. Lan, M. and Naerheim, Y., 1986, In-process detection of tool breakage in milling, *ASME Journal of Engineering for Industry*, 108, August, 191–197.
38. Altintas, Y., Yellowley, I., and Tlusty, J., 1988, The detection of tool breakage in milling operations, *ASME Journal of Engineering for Industry*, 110, 3, 271–277.
39. Sata, T., Matsushima, K., Nagakura, T., and Kono, E., 1973, Learning and recognition of the cutting states by the spectrum analysis, *Annals of the CIRP*, 22, 41–42.
40. Danai, K. and Chin, H., 1991, Fault diagnosis with process uncertainty, *ASME Journal of Dynamic Systems, Measurement and Control*, 113, 3, 339–343.
41. Colgan, J., Chin, H., Danai, K., and Hayashi, S., 1994, Tool breakage detection in turning: a multisensor method, *ASME Journal of Engineering for Industry*, 116, 1, 117–123.
42. Tansel, I. N. and McLaughlin, C., 1991, On-line monitoring of tool breakage with unsupervised neural networks, *Transactions of NAMRC*, SME, 364–370.
43. Jammu, V. B. and Danai, K., 1993, Unsupervised neural network for tool breakage detection in turning, *Annals of the CIRP*, 42, 1, 67–70.
44. Delio, T., Tlusty, J., and Smith, S., 1992, Use of audio signals for chatter detection and control, *ASME Journal for Manufacturing Scientists and Engineers,* 119, 146–157.
45. Schofield, S. and Wright, P., 1998, Open architecture controllers for machine tools, Part 1: Design principles, *ASME Journal for Manufacturing Scientists and Engineers,* 120, 417–424.
46. Koren, Y., 1997, Control of machine tools, *ASME Journal for Manufacturing Scientists and Engineers,* 119, 749–755.
47. Masory, O. and Koren, Y., 1985, Stability analysis of a constant force adaptive control system for turning, *ASME Journal of Engineering for Industry*, 107, 1, 295–300.
48. Daneshmend, L. K. and Pak, H. A., 1986, Model reference adaptive control of feed force in turning, *ASME Journal of Dynamic Systems, Measurement, and Control*, 108, 1, 215–222.
49. Lauderbaugh, L. K. and Ulsoy, A. G., 1988, Dynamic modeling for control of the milling process, *ASME Journal of Engineering for Industry*, 110, 4, 367–375.
50. Tomizuka, M. and Zhang, S., 1988, Modeling and conventional adaptive PI control of a lathe cutting process, *ASME Journal of Dynamic Systems, Measurement, and Control*, 110, December, 350–354.
51. Rober, S. J. and Shin, Y. C., 1996, Control of cutting force for end milling processes using an extended model reference adaptive control scheme, *ASME Journal for Manufacturing Scientists and Engineers,* 118, 339–347.
52. Hsu, P.-L. and Fann, W.-R., 1996, Fuzzy adaptive control of machining processes with a self-learning algorithm, *ASME Journal for Manufacturing Scientists and Engineers,* 118, 522–530.
53. Liang S. Y. and Perry, S. A., 1994, In-Process Compensation for Milling Cutter Runout via Chip Load Manipulation, *ASME Journal of Engineering for Industry,* 116, 153–160.
54. Furness, R. J., Ulsoy, A. G., and Wu, C. L., 1996, Feed, speed, and torque controllers for drilling, *ASME Journal for Manufacturing Scientists and Engineers,* 118, 2–9.
55. Nachtigal, C. L. and Cook, N. H., 1970, Active control of machine-tool chatter, *ASME Journal of Basic Engineering*, 92, 2, 238–244.
56. Mitchell, E. E. and Harrison, E., 1977, Design of a hardware observer for active machine tool control, *ASME Journal of Dynamic Systems, Measurement, and Control*, 99, 227–232.

57. Subramanian, T. L., DeVries, M. F., and Wu, S. M., 1976, An investigation of computer control of machining chatter, *ASME Journal of Engineering for Industry*, 98, 1209–1214.
58. Li, C. J. and Li, S. Y., 1992, On-line roundness error compensation via P-integrator learning control, *ASME Journal of Engineering for Industry,* 114, 476–480.
59. Tsao, T.-C. and Tomizuka, M., 1987, Adaptive zero phase error tracking algorithm for digital control, *ASME Journal Dynamic Systems, Measurement, and Control*, 109, 349–354.
60. Tung, E. D., Tomizuka, M., and Urushisaki, Y., 1996, High-speed end milling using a feedforward control architecture, *ASME Journal for Manufacturing Scientists and Engineers,* 118, 178–187.
61. Ermer, D. S., 1997, A century of optimizing machining operations, *ASME Journal for Manufacturing Scientists and Engineers,* 119, 817–822.
62. Centner, R., 1964, Final report on development of adaptive control technique for numerically controlled milling machining, USAF Tech. Documentary Report ML-TDR-64-279.
63. Amitay, G., Malkin S., and Koren, Y., 1981, Adaptive control optimization of grinding, *ASME Journal of Engineering for Industry*, 103, 1, 102–111.
64. Koren, Y., 1989, The optimal locus approach with machining applications, *ASME Journal of Dynamic Systems, Measurement, and Control*, 111, 1, 260–267.
65. Furness, R. J., Ulsoy, A. G., and Wu, C. L., 1996, Supervisory control of drilling, *ASME Journal for Manufacturing Scientists and Engineers,* 118, 10–19.
66. Xiao, G., Malkin S., and Danai, K., 1993, Autonomous system for multistage cylindrical grinding, *ASME Journal of Dynamic Systems, Measurement, and Control*, 115, 4, 667–672.
67. Ivester, R. W. and Danai, K., 1996, Intelligent control of machining under modeling uncertainty, *CIRP Manufacturing Systems*, 25, 1, 73–79.
68. Ivester, R., Danai, K., and Malkin, S., 1997, Cycle time reduction in machining by recursive constraint bounding, *ASME Journal for Manufacturing Scientists and Engineers,* 119, 2, 201–207.
69. Ko, T. J. and Cho, D. W., 1998, Adaptive optimization of face milling operations using neural networks, *ASME Journal for Manufacturing Scientists and Engineers,* 120, 443–451.
70. Azouzi, R. and Guillot, M., 1998, On-line optimization of the turning process using an inverse process neurocontroller, *ASME Journal for Manufacturing Scientists and Engineers,* 120, 101–108.